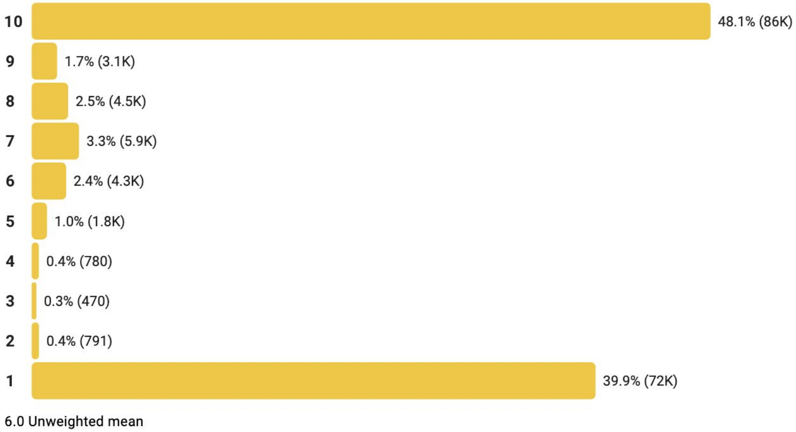
Review Bombing & Film Recommendations

By: Kai Chang, Oliver Stewart, Samia Jaman, and Justin Lederer



Review Bombing & Film Recommendations

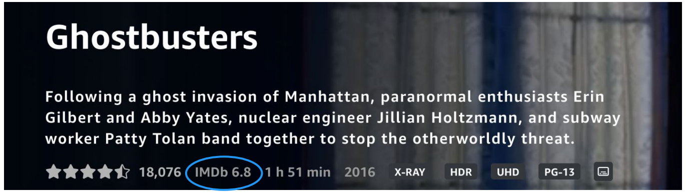
The Movie Business Context

- US domestic box office exceeded $1.6B in early 2025
- Annual gross: $8.5-9B (excluding streaming/rentals)
- Online ratings now overshadow traditional critics

Review Bombing: The Problem

Coordinated online communities mass-rating films (usually negatively) to manipulate scores

- Targets films with diverse casting or political content
- Impacts recommendation algorithms
- Perpetuates representational harms



Research Questions & Findings

Research Questions:

- What kinds of movies does IMDb's weighting algorithm boost/de-boost?
- How do different weightings affect recommendation algorithms?
- What weighting algorithm best offsets review-bombing effects?

Key Findings:

Boosted Movies:

- Political thrillers
- Historical/biographical films
- Controversial subject matter
- High-brow cinema

Deboosted Movies:

- Family/romance films
- Mainstream entertainment
- Teen/young adult content
- Action/video game adaptations

Dataset Overview

IMDb Dataset Components

Scraped from IMDb website and GraphQL API → *imdb-cleaned.csv*

Basic Movie Information:

- Title, genre(s), release year
- Plot keywords
- Total votes
- Rating breakdown (1-10)
- Top 5 voting countries

Calculated Metrics:

- Unweighted rating (mean)
- Rating difference (weighted vs. unweighted)
- Polarization score (Esteban-Ray index)
- Country rating differences
- 2-9 rating (excluding extremes)

Dataset filters: Only movies with ≥50,000 user votes included

Analysis focus: Rating polarization as indicator of potential review bombing

Highlights from EDA — Polarizing films

These US-released films received the highest scores on our polarization metric, which indicates a non-unimodal ratings distribution and therefore a more controversial or polarizing film.

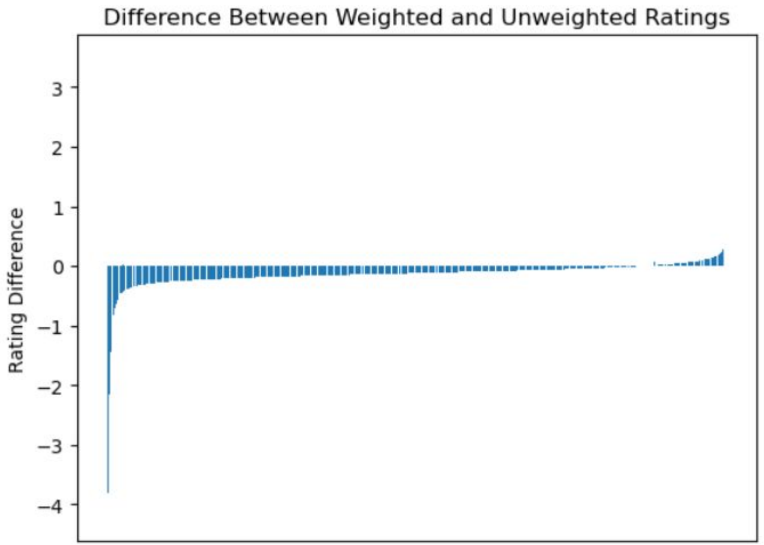
	id	title	genres	weighted_rating	release_year	gross	rating_1	rating_2	rating_3	rating_4
3314	tt4776998	The Promise	Action,Adventure,Drama	6.1	2017	8224288	71664	785	464	775
4283	tt6277462	Brahmastra Part One: Shiva	Action,Adventure,Fantasy	5.6	2022	7839108	42059	3965	2358	2499
3628	tt26932223	Bhool Bhulaiyaa 3	Comedy,Fantasy,Horror	4.7	2024	2230000	22601	5180	4905	3708
4172	tt10028196	Laal Singh Chaddha	Comedy,Drama,Romance	5.6	2022	3401324	97775	4265	1436	973
4106	tt10083340	Gangubai Kathiawadi	Biography,Crime,Drama	7.8	2022	592000	16466	1161	763	856
4055	tt12844910	Pathaan	Action,Adventure,Thriller	5.8	2023	17487476	36924	3847	3083	3522
1989	tt0312528	The Cat in the Hat	Adventure,Comedy,Family	4.1	2003	101149285	11292	7248	8036	8329
2418	tt13751694	Animal	Action,Crime,Drama	6.1	2023	15004482	17253	3175	2982	3450
567	tt5971474	The Little Mermaid	Adventure,Family,Fantasy	7.2	2023	298172056	42723	8622	6100	6535
2322	tt0240515	Freddy Got Fingered	Comedy	4.7	2001	14254993	11087	4147	3884	4137

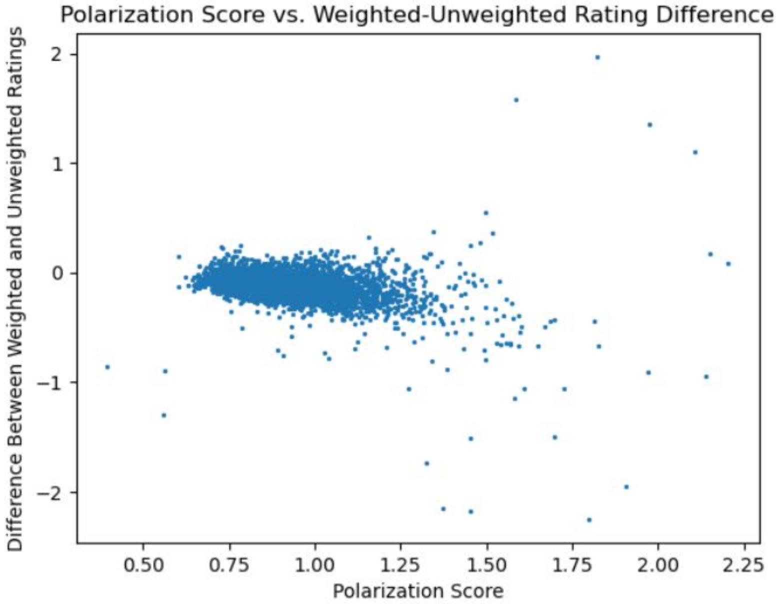
Highlights from EDA — Weighted ratings

These US-released films had the highest (positive) gaps between their weighted and unweighted ratings, meaning that IMDb's weighting adjustment algorithm identified unusual voting activity and increased the film's score accordingly.

	id	title	genres	weighted_rating	release_year	gross	rating_1	rating_2	rating_3	rating_
567	tt5971474	The Little Mermaid	Adventure,Family,Fantasy	7.2	2023	298172056	42723	8622	6100	653
2127	tt1289401	Ghostbusters	Action,Comedy,Fantasy	6.8	2016	128350574	43927	13107	14645	2079
4106	tt10083340	Gangubai Kathiawadi	Biography,Crime,Drama	7.8	2022	592000	16466	1161	763	85
4172	tt10028196	Laal Singh Chaddha	Comedy,Drama,Romance	5.6	2022	3401324	97775	4265	1436	97
2826	tt10298810	Lightyear	Animation,Action,Adventure	6.1	2022	118307188	23434	3069	3433	562
1119	tt2527336	Star Wars: Episode VIII - The Last Jedi	Action,Adventure,Fantasy	6.9	2017	620181382	51466	19465	23687	3162
2368	tt8093700	The Woman King	Action,Drama,History	6.9	2022	67328130	10438	1949	1318	171
3820	tt0019254	The Passion of Joan of Arc	Biography,Drama,History	8.1	1928	21877	2656	847	916	123
112	tt11315808	Joker: Folie à Deux	Drama,Musical,Thriller	5.2	2024	58300287	24956	9511	12110	1662
730	tt10676048	The Marvels	Action,Adventure,Fantasy	5.5	2023	84500223	20877	7278	8546	1194

Highlights from EDA — Key visualizations





In general, as the first visualization shows, most adjustments made by IMDb's weighting algorithm were negative—that is, most films had their ratings lowered by weighting, although usually by a small amount. The second visualization demonstrates that more polarized films were more heavily adjusted by the weighting algorithm, although absolute rating difference, which we looked at later, offers a clearer view of this.

Methods — Calculating polarization

Adapting Esteban and Ray (1994)’s polarization algorithm

- Our goal: Calculate the polarization of films’ rating distributions as a proxy for review bombed films.
- We will do this by using an adapted version of an algorithm laid out by economists Joan Esteban and Debraj Ray.
    - In short, the formula calculates the difference between each pair of ratings, multiplied by the frequency of those ratings. Our scale is adjusted to a scale from 0 to 1 for ease of interpretation.
    - A film with all 10 ratings would have a polarization score of 0; a film with half 1s and half 10s would score 1.

```
def calc_polarization(row):
    total_score = 0
    for rating_1 in range(1, 11):
        for rating_2 in range(rating_1 + 1, 11):
            total_score += row[f'rating_{rating_1}'] / row['total_votes'] * row[f'rating_{rating_2}'] / row['total_votes']* (rating_2 - rating_1)

    return total_score
```

Our version of Esteban and Ray’s polarization algorithm, implemented in our EDA. This score, based on the data on film ratings from 1 through 10 that we scraped from IMDb, is one of the key elements of our analysis.

Methods — Naive recommendation system

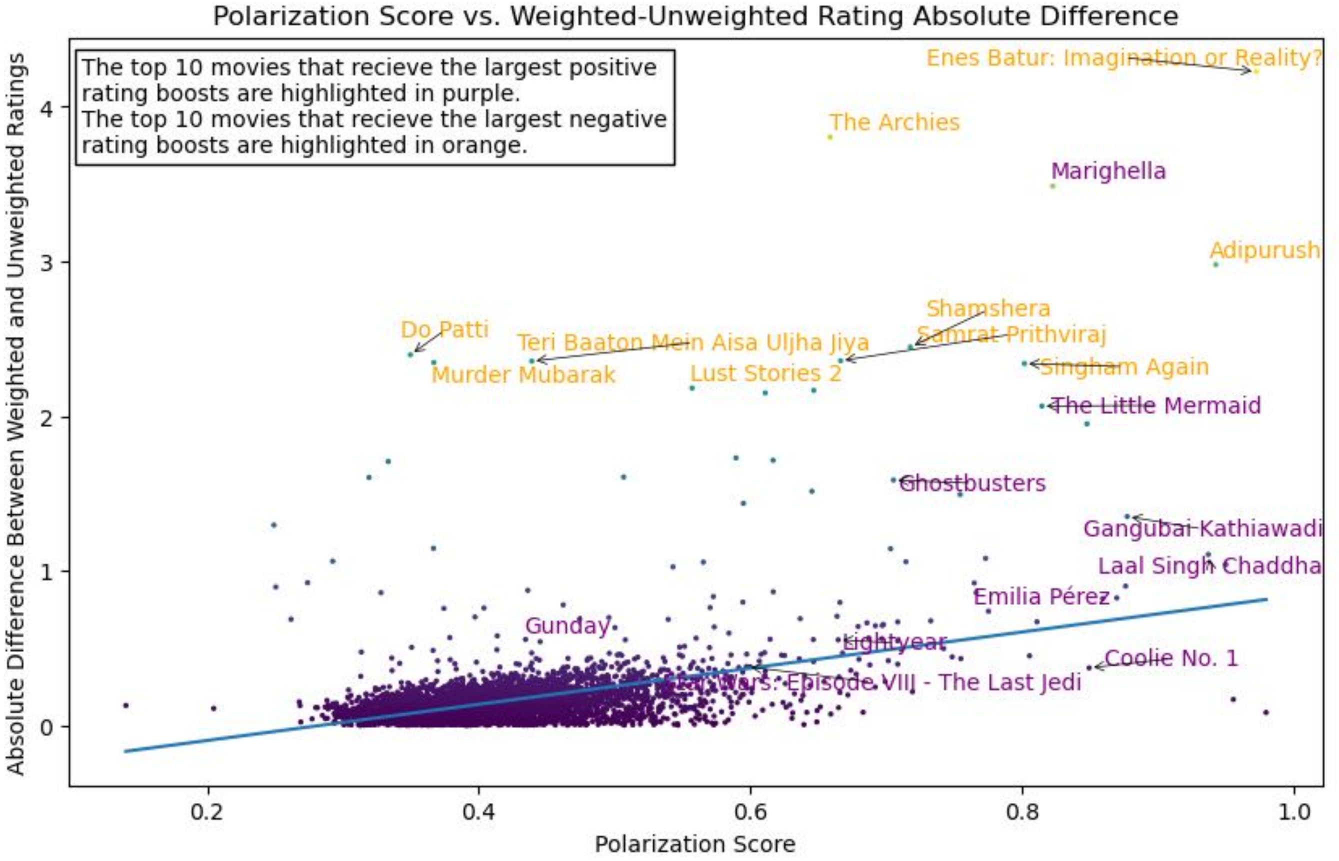
Mimicking movie recommendation systems using plot keywords and ratings

- Key harm of review bombing: potential to damage films' prospects by lowering their chances to be recommended.
- To understand this, we worked on a simplified version of a film recommendation system.
    - IMDb provides a list of "plot keywords" for each film alongside the ratings.
    - Our system gives films recommendation scores relative to a "base film" by multiplying the proportion of shared keywords by the film's rating.
- By measuring how likely a film is to be recommended before and after the score is weighted, we aim to understand how IMDb's weighting impacts films' recommendation chances.

```
def naive(movie, movies_not_me, rating_column):
    movie_keywords = set(movie.keywords)

    matching_keyword_score = movies_not_me['keywords'].apply(lambda x: len(movie_keywords.intersection(set(x)))) /len(movie_keywords) * 10
    rating_score = movies_not_me[rating_column]

    recommendation_score = matching_keyword_score * rating_score

    return recommendation_score
```

The algorithm for generating film recommendations as implemented in our preliminary report notebook. The effects of weighting on recommendation will be explored further in the section on results.

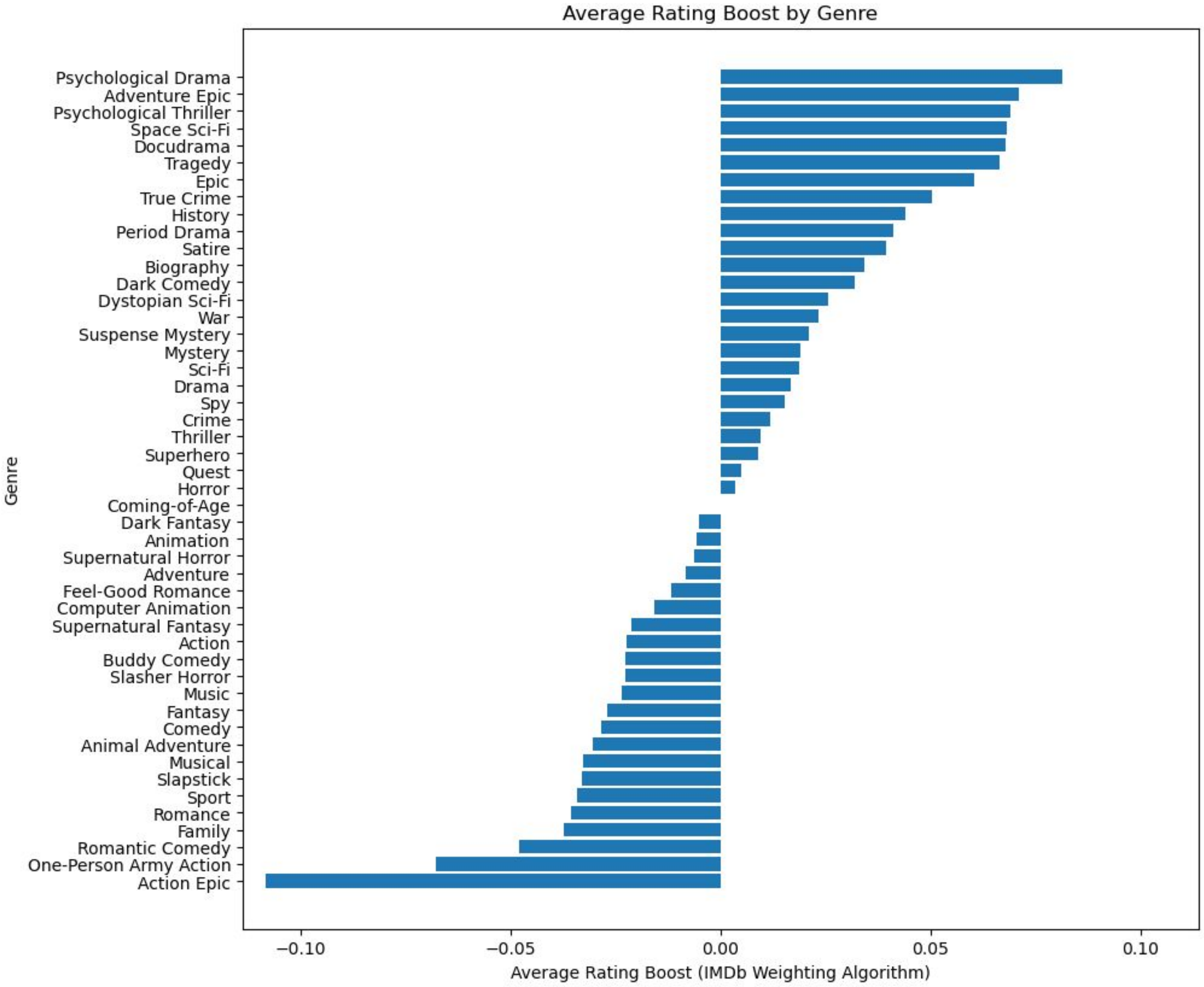
Analysis - Polarization Score vs. Weighted Rating Absolute Difference



Findings - Weighting Algorithm Effect by Genre

Psychological, Sci-Fi, Non-fiction

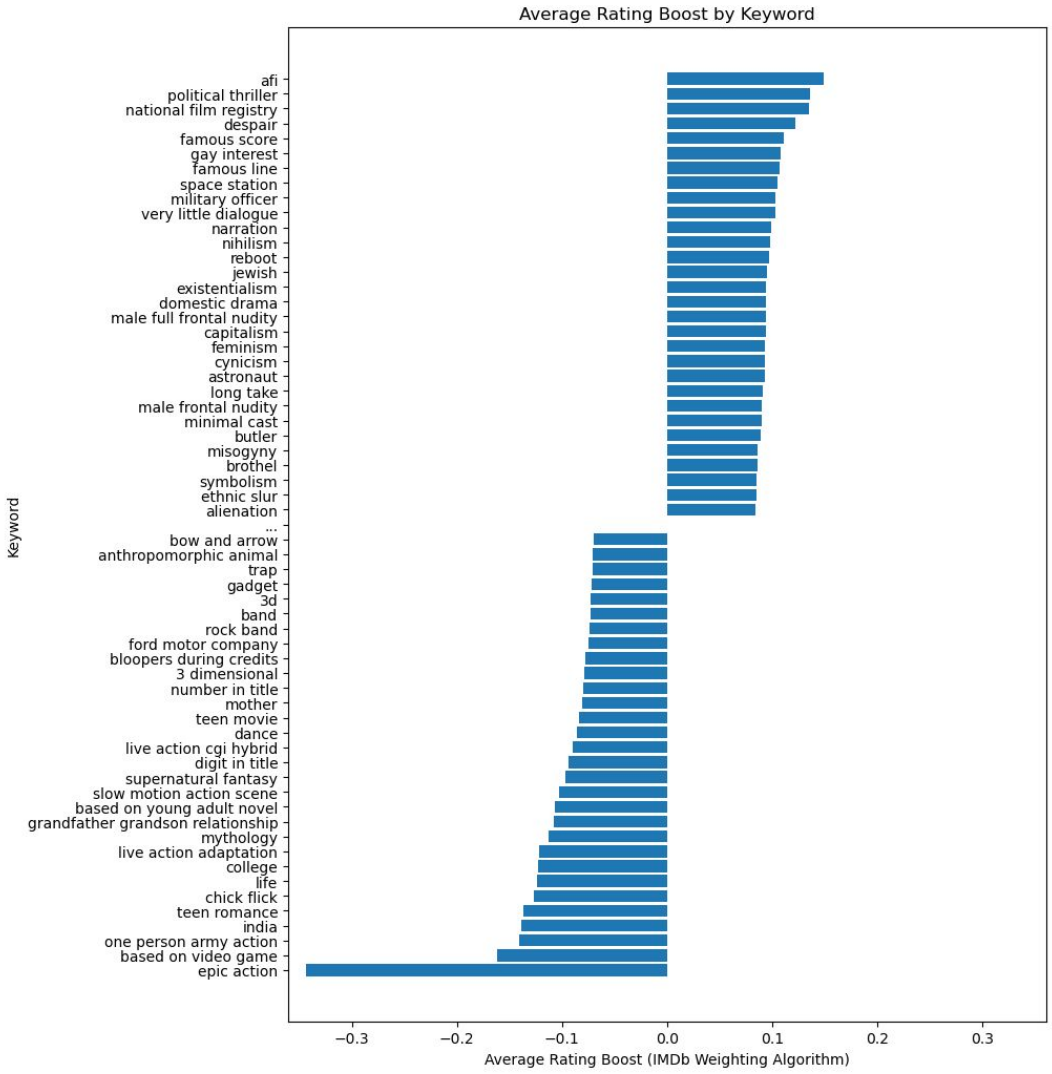
Action, Romance



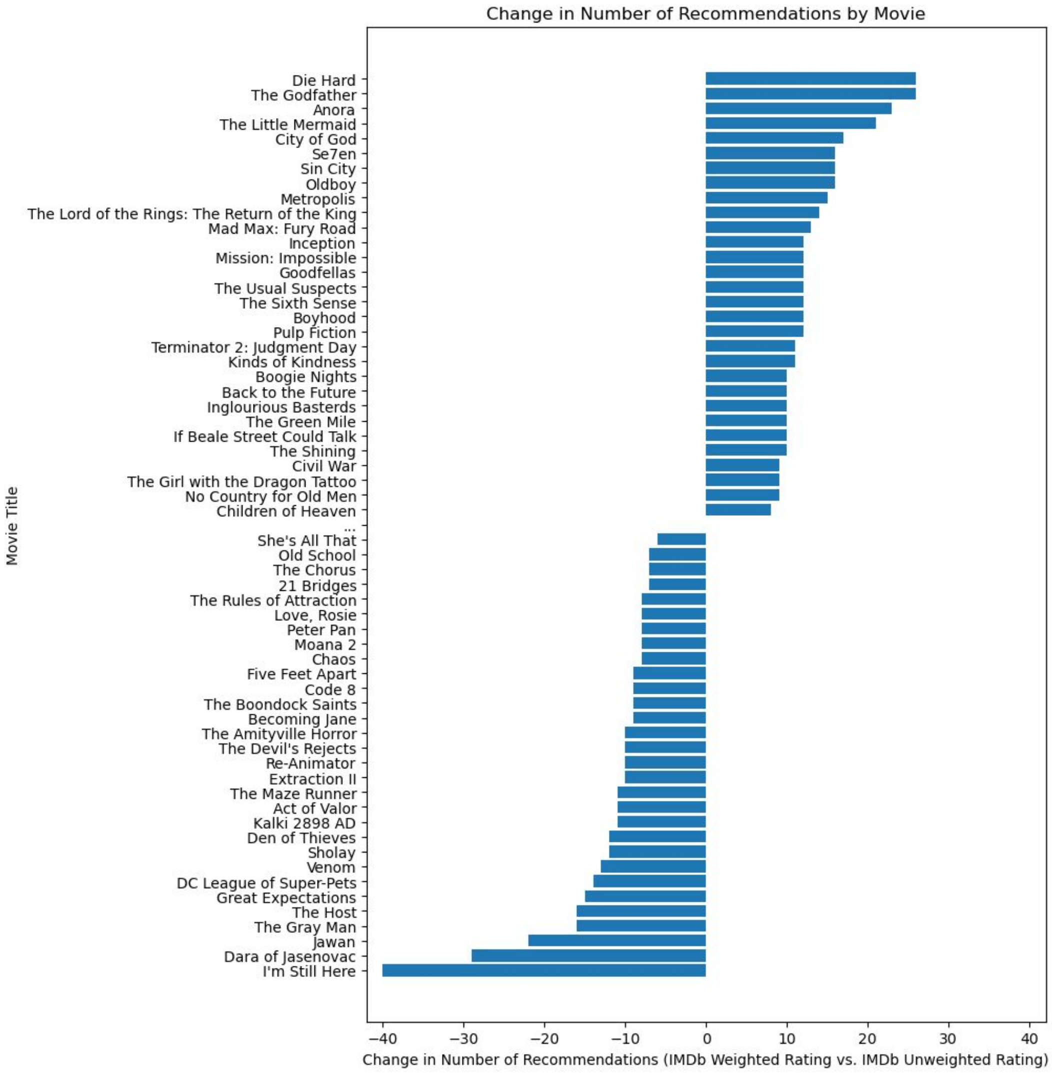
Findings - Weighting Algorithm Effect by Keyword

Highbrow, Controversial Themes

Lowbrow, Adaptations, Action, Romance



Findings - Naive Recommendation System



Discussion

Polarized Movies Attract Review Bombing

- More polarized keywords affect weighting
- Recommender didn’t line up with hypothesis
- More “controversial” keywords received weighted rating boost
- Can assume movies with more “polarized” keywords more likely to receive review bombing
- Hard to predict if specific movie will be review bombed

Future Work

Future Research Questions:

- Will review bombing have a tangible effect on box office performance?
- How does the region affect distribution of ratings?
- Does cast diversity or having a director/lead of a marginalized identity attract review bombing?

Possible Datasets:

- Box Office Data (US)
- IMDB Countries